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Cover Page Footnote

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Performance of Active Extension Strategies: Evidence from the Australian Equities Market

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Abstract

This study examines the performance of several active extension strategies, commonly known as 130/30, in the Australian equities market. A detailed analysis of the factors affecting performance is explored using Monte Carlo simulations based on eight years of historical returns for the constituents of the S&P/ASX 200 index under a variety of realistic cost assumptions. We find evidence of a statistically significant increase in performance of active extension strategies over equivalent long-only portfolios, holding all other factors constant. The observed increase is highest for managers with greater levels of skill, where any tracking error limit is high and total costs are low. This is one of the first studies in the Australian market and is expected to have a high degree of relevance to institutional investors considering active extension strategies.

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JEL Classification: G11, G17

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Introduction

The long-only constraint remains the most common and binding of all portfolio constraints imposed on fund managers. Restricting short sales prevents managers from fully implementing their complete information set when constructing their portfolios. Recently, a portfolio structure known as '130/30' or 'active extension' has come into favour among investment funds, by relaxing the short-selling constraints associated with long-only portfolios. This provides fund managers with exposure to market returns unavailable to market neutral long-short portfolios. In theory, relaxing the short-selling constraint allows investors to construct more efficient portfolios that generate higher performance on a risk-adjusted basis. However, increasing short-selling also increases costs relating to turnover, borrowing stock and financing which act as a drag on portfolio performance. Previous research focused on the US equities market has proposed that the increased performance of active extension portfolios outweigh the costs, leading to higher risk-adjusted performance. This study aims to verify that this proposition holds true for the Australian equities market under several realistic cost assumptions. Furthermore, our research quantifies the sensitivity of performance to a number of endogenous and exogenous factors such as the level of manager skill, risk target, costs and benchmark characteristics.

Active extension funds have considerable appeal in the Australian context due to higher level concentration in the S&P/ASX 200 benchmark, lower regulatory restrictions on the amount of leverage that can be employed by retail funds and a highly liquid market for borrowing stock. Many active extension strategies have only been created in the past five to ten years in the US and Europe and experienced rapid growth rates.[4] Although active extension portfolios are not yet as common in the Australian market as they are in the US or Europe, some Australian superannuation funds have followed the lead of pension funds in these markets in providing active extension strategies to investors. Considering the growing uptake in active extension strategies by superannuation funds and other institutional investors, an analysis of the performance of active extension strategies is also of prime importance to these participants. Given the lack of previous research directed towards the Australian market, there is considerable scope for academic research into quantifying the benefits of active extension strategies within the Australian equities market.

The remainder of this study is organised as follows. The second section provides an overview of active extension strategies. The third section reviews the literature that examines the performance of active extension strategies. This is followed by a description of hypotheses to be tested. The fifth section describes the data and method. The sixth section provides and discusses the results and the seventh section concludes.

An Overview of Active Extension Strategies

Active extension portfolios provide an effective blend of long-only funds and market-neutral hedge funds (see Appendix 1), allowing managers to pursue short-selling opportunities to potentially increase portfolio alpha (i.e., benchmark outperformance) while simultaneously retaining an exposure to overall market returns. In recent years, a portfolio structure known as '130/30' or 'active extension' has become increasingly common. In this type of portfolio, securities to 30% of the value of the fund are short-sold, with the sale proceeds reinvested into

[4] For example, the funds under management for active extension strategies grew by 77% over a twelve month period to September 2007 (Pensions & Investments 2007)

the long side of the portfolio. On a net basis the portfolio has a 100% exposure to the market and often has a target beta of one. This portfolio structure presents a hybrid of the market exposure that traditional long-only portfolios have with the ability of a long-short fund to take short positions. Although the name '130/30' is commonly used to describe this portfolio structure, it is often used as a generic term for active extension portfolios with different amounts of leverage. As the '130/30' label suggests, a short-selling level of 30% is most commonly used for these strategies, although this may not represent the optimal level of short-selling. In practice, the optimal level varies depending on factors such as level of managerial skill, risk targets, total costs and benchmark characteristics.

The prime benefit of relaxing the short-sale constraint is the ability to take full advantage of negative information about a security. With a short-selling constraint imposed, long-only managers are restricted from efficiently implementing their "sell ideas" into the portfolio. In this scenario, a fund manager's minimum position in a security is a zero holding. Relative to the index position, the maximum underweight that can be undertaken by active managers is the negative of the index weight. Relaxing the long-only constraint improves the ability of a manager to implement their negative views on a stock by increasing their potential to take larger underweight positions to benefit from stocks they expect to underperform. The proceeds earned from this underweighting are subsequently directed into a portfolio's buy positions. In the case of a 130/30 portfolio for example, a 30% overweight in long positions of stocks expected to outperform the market allows fund managers to increase exposure in undervalued stocks.

The benefit from relaxing the short-sale constraint is highly related to the level of benchmark concentration. Benchmark concentration refers to the large proportion of an index made up of a small number of stocks with large market capitalisations.[5] For example, the largest 12 stocks in the S&P/ASX 200 index represent 50% of the benchmark by capitalisation, with the remaining 189 stocks comprising the remaining 50%. Only the largest 21 stocks in the index have an index weight above 1%, with the bottom 179 having benchmark weights below 1%.[6] In a long-only context, it is difficult to achieve a meaningful underweight position in these stocks with a restriction on short-selling in place, thereby reducing the manager's ability to construct efficient portfolios. This view is consistent with Foley (2006).

Some argue that active extension portfolios are inherently more risky than long-only portfolios as a result of their higher gross exposure (Patterson 2006). Although increasing gross market exposure of managed funds by incorporating extra short-side and long-side positions to a portfolio intuitively appears to increase risk, this is not necessarily the case. An active extension portfolio can be constructed with the same level of risk as a long-only portfolio using the same set of forecast returns. In Section 6, we show that on average this leads to higher risk-adjusted returns from active extension portfolios before adjusting for costs. Since increasing the level of short positions involves an additional yet equal increase to the long positions, the systematic risk from shorting is offset. The increase in residual risk may be mitigated in portfolio construction

[5] Benchmark concentration in the Australian market is more pronounced than in other developed markets due in part to the large weighting of BHP Billiton, Rio Tinto, Woolworths and the four major banks. Applying the metric of benchmark concentration (i.e. the Gini coefficient used by Grinold & Kahn 2000) to the S&P/ASX 200 gives a value of 0.85, compared to 0.80 for the S&P 500, 0.81 for the FTSE 100 and 0.81 for the Eurostoxx 300. These results suggest that the Australian market has a higher degree of benchmark concentration relative to other major indexes of developed markets.

[6] The information provided was sourced from Bloomberg as of 2 May 2008.

by proportionally reducing the size of other active positions[7]. The ability to incorporate short-side information into active extension portfolios allows for an increase in performance with the same level of risk (as measured by tracking error).[8]

Literature Review

There are a number of studies, which measure the efficiency of portfolio implementation. The seminal piece of work in this area began with Grinold (1989), who introduced the 'fundamental law of active management' equation as:

$$IR = IC.\sqrt{N} \tag{1}$$

where IR is the observed information ratio, a measure of risk-adjusted outperformance[9], IC is the information coefficient given by the correlation of forecast security returns with realised security returns, and N is the number of securities in the investment universe. Although Grinold (1989) acknowledges that the fundamental law is approximate in nature, the important intuition is that returns are a function of information level, breadth of investment universe and portfolio risk.

Clarke, de Silva and Thorley (2002) extend the seminal ideas of Grinold (1989) by introducing the idea of a transfer coefficient (TC) to measure the efficiency of portfolio implementation. The transfer coefficient measures how efficiently forecast returns are implemented in portfolio construction. A simplifying assumption of the Grinold (1989) framework is that managers have no restrictions on how they can construct a portfolio from the information set they possess. Within an adjusted Grinold (1989) framework, IR is equal to:

$$IR = TC.IC.\sqrt{N} \tag{2}$$

From Eq. 2, the transfer coefficient acts as a scaling factor on the level of information. This is an important result, as it infers that portfolio outperformance is driven not only by the ability to forecast security returns but also by the ability to frame those security returns in the form of an efficient portfolio. The implication is that managers who are skilled at forecasting security returns need to be able to construct an efficient portfolio to maximise the benefit from their information set. Assuming the construction of an efficient portfolio in the absence of any constraints the transfer coefficient will be equal to one. Constraints on portfolios lower the transfer coefficient as they place limits on how efficiently managers can construct portfolios that reflect their forecasts.

7 Active positions (weights) are defined as the portfolio weight in a security less the benchmark weight, and provide a measure of portfolio weighting relative to a benchmark. With the long-only constraint in place, the smallest position it is possible to have in an individual stock is to not hold it, and hence the lowest active weight possible to have in a single stock is the negative of its benchmark index weight.

8 Tracking error refers to the standard deviation of portfolio returns against the benchmark return. In this context, risk refers to the deviation of the portfolio returns from the benchmark returns. The use of tracking error as a measure of portfolio risk is common through industry and in the active management literature (Grinold &Kahn 2000).

9 The main performance measure used to measure portfolio performance is risk-adjusted performance, measured by the information ratio of the portfolio. Information ratios are defined as excess return over the benchmark, divided by tracking error.

Clarke et al. (2002) also extend their analysis with a Monte Carlo simulation of example portfolios constructed from the constituents of the S&P 500, subject to a set of constraints. The effect of size-neutrality, sector neutrality, value-growth neutrality, maximum total number of positions and long-only constraints are analysed. Clarke et al. (2002) find that the long-only constraint is the most significant restriction placed on portfolio managers, but by nature of its ubiquity remains ignored as a constant that affects portfolio construction. In a later study, Clarke, de Silva and Sapra (2004) find that short sale constraints in a long-only portfolio cause the most significant reduction in portfolio efficiency.

In comparing the additional costs and benefits associated with an active extension structure compared to a long only portfolio, Sorensen, Hua and Qian (2007) conclude that the long-only constraint impedes the ability of fund managers to outperform their target benchmarks. The authors specifically examine the optimal level of short selling and show it to be a function of manager skill, the desired risk target, turnover, leverage and trading costs. Most importantly, they find that there is no universal optimal level of short selling in an active extension portfolio. Rather, the required level of short selling varies according to different factors and market conditions.

Clarke et al. (2008) develop a mathematical model that computes the expected level of short positions for the portfolio. The authors empirically show that an increase in benchmark concentration and pair-wise correlation between stocks increases the expected level of short selling, while an increase in market volatility decreases the desirable level of shorting.

Hypothesis Development

In this section, the development of hypotheses relating the performance of active extension portfolios to unique factors ranging from characteristics of the specific fund manager to overall market conditions are presented.

Skill Levels

Theoretically, managers with higher skill levels are able to benefit more from relaxing the long-only constraint (Sorensen et al. 2007). Increasing the short selling level has a net benefit only if the increase in outperformance is greater than the increase in cost burden. Managers with greater skill are able to undertake greater short selling levels until the additional transaction and financing costs outweigh the marginal benefits. Foley (2006) notes that in the case where a manager has no stock picking skill ($IC \approx 0$) the optimum level of short selling will be zero, since increasing short selling levels will only result in higher costs. In the case where a manager has some predictive skill ($IC > 0$), the manager will be able to transform larger active weights into greater outperformance, leading to a higher level of performance from active extension strategies as they utilise the manager's informational advantage.

H1: Managers with higher skill levels have a greater increase in performance from relaxing the long-only constraint.

Skew in Predictive Ability

One of the barriers to successful implementation of active extension strategies identified by Gastineau (2008) is the ability of the manager to be able to pick stocks that can potentially underperform in addition to picking stocks that can outperform. Managers who have previous stock-selection experience in managing long-only portfolios are likely to have developed greater skills in identifying potential outperformers than potential underperformers. Intuitively, being able to pick potential underperformers is a key concern when managing a portfolio that involves short selling.

H2: Managers with a higher skew towards picking underperforming stocks can construct active extension portfolios with higher levels of performance

Risk Constraints

Portfolio managers usually have some form of risk constraint placed on them by investors or fund administrators in the form of a limit (target) to tracking error. The size of a tracking error is a function of portfolio active weights and the variance-covariance matrix. In general, the tracking error of a portfolio will be proportional to the gross size of active weights. As Jacobs and Levy (2006) identify, a portfolio with a low tracking error targets such as an enhanced index fund will likely have weights close to the index and is not restricted by the long-only constraint. Funds with higher tracking error targets will have higher active weight positions as managers are able to take larger overweight and underweight positions within the risk target. As the active weight sizes are increased, managers are more likely to run up against the short-sale constraint when implementing their underweight positions. In a long-only portfolio, managers concentrate their portfolios by holding large positions in their favourite stocks, but are restricted on the short side from being unable to negatively gear their least favourite stocks. Funds with higher tracking error targets are more likely to be constrained by a long-only requirement and will gain the greatest increase in transfer coefficient from relaxing the long-only constraint. As Clarke et al. (2004) note, there is a trade-off between the maximum transfer coefficient, target tracking error and level of shorting. If the portfolio has a higher tracking error target, a higher level of short selling is needed to maximise the transfer coefficient.

H3: Portfolios with higher tracking error targets experience greater performance increase from relaxing the long-only constraint.

Costs

Transaction, financing and stock borrowing costs increase proportionally to the gross exposure of the fund, which is driven by the level of short selling in the portfolio. A higher cost base acts as a drag on net of cost portfolio performance, decreasing the benefits from an active extension strategy. Higher costs should decrease the attractiveness of higher levels of gross exposure, leading to a lower optimum shorting level. Whether the decrease in the optimal level of shorting is material depends on the level of costs versus managerial skill.[10]

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[10] It should be noted that costs are partly endogenous to the extent that trading is discretionary.

H4: An increase in costs relative to the skill the manager possesses will at some point lower the performance of active extension strategies.

Volatility

One of the consequences of a high risk target in long-only funds is that managers create portfolios with weightings concentrated in their best overweight selections. Montagu, Cahan and Morton (2007) argues that in more volatile markets, greater portfolio concentration may expose a portfolio to higher risk due to lower diversification. An active extension strategy by contrast, allows for a lower risk target for the same return by using short-side information in a portfolio with added diversification, achieving a higher risk-return outcome. In a higher volatility environment the benefits of increased diversification should increase the net benefit of increasing short-selling, leading to higher risk-adjusted returns for active extension portfolios.

H5: Higher market volatility will increase the performance of active extension strategies.

Cross-sectional Spread of Returns

Over the past decade, a decrease in the cross-sectional spread (dispersion) of individual stock returns on the S&P/ASX 200 has been found (Montagu et. al.,2007). This decrease is associated with a sharp increase in pairwise correlations between individual stock returns.[11] An argument put forward by Grinold and Kahn (2000) and Clarke et al. (2008) is that in environments of higher correlation between individual security returns, larger active positions are needed to achieve the same target level of outperformance. If managers are required to increase their active weight sizes in environments of low cross-sectional dispersion, they will be more highly constrained by the long-only requirement. Accordingly, they will benefit more from introducing short positions into their portfolios. A higher level of short selling will allow managers to more efficiently distribute their higher active weights over both long and short positions in the portfolio to target a higher excess return for the same level of risk.

H6: Active extension portfolios perform better in comparison to long-only portfolios in periods where individual stock returns are more highly correlated

Market Conditions

There is no evidence or theoretical basis to suggest that active extension portfolios will perform better or worse in rising or falling markets. By definition, active extension portfolios have a constant 100% net market exposure and will have a beta approximating one if well diversified, and thus on average will perform in line with the broader market. Bear market conditions, defined as periods where market returns are below their long-term average, may be associated with changes in related exogenous factors such as market volatility, cross-sectional spread of returns or higher transaction costs due to lower liquidity. Apart from the effects of these factors, when all other factors are held equal, declines or increases in the broader market should not be

[11] This study finds that the average pair-wise correlation of securities in the S&P/ASX200, calculated using rolling 12-month periods, has increased over the sample period analysed (i.e. May 2000 to July 2008)

expected to have an impact on the ability of active extension strategies to outperform (or underperform) the broader market.

H7: The level of outperformance or underperformance of active extension portfolios is equivalent across periods of positive or negative market returns.

Data and Method

Data on historical stock returns and index weightings is obtained from IRESS. The analysis encompasses all stocks in the S&P/ASX 200 index from May 2000 to July 2008, including stocks added or removed due to index rebalancing by Standard and Poor's (S&P). The sample covariance matrix was constructed from five years of monthly returns prior to May 2000. The S&P/ASX 200 index is chosen due to the liquidity of its constituents and the greater availability and lower cost of borrowing stock relative to less liquid securities outside the index. Total shareholder returns are used for the analysis to include the value of dividends, and accordingly portfolio performance is benchmarked against the S&P/ASX 200 Accumulation index.

Theoretical portfolios are constructed based on historical returns data from the top 200 stocks by market capitalisation listed on the Australian Securities Exchange (ASX). Monte Carlo simulations of multiple portfolios with different levels of short-selling provide a back test of how active extension portfolios performed over the previous eight year period. To test these hypotheses, the effect of changes in factors such as forecasting skill, skew in predictive ability and trading costs are varied, and the subsequent changes in portfolio performance over various levels of short selling are analysed. The following discussion explains the portfolio construction techniques for the Monte Carlo simulation.

The stock selection method is based on a quantitative forecasting procedure proposed by Grinold and Kahn (2000) that is related to the fundamental law of active management. To create each set of forecasted returns for the top 200 stocks, returns are drawn from a normal distribution with a set correlation to realised returns for that period. The correlation of forecasted returns to realised returns is equal to the information coefficient, which allows for the specific ex-ante predictive ability of the stock selection model to be set for each portfolio. In essence, this involves creating forecasts by adding noise to realised returns to mimic an active manager with some forecasting skill.

An approach suggested by Qian, Hua and Sorensen (2007a) is to incorporate the effects of transaction costs into the stock selection model. Portfolio turnover comes from two sources: the need to rebalance portfolios back to target weights due to security price movements, and changes in forecasts necessitating changes in portfolio weights. To implement this, generated forecasts have an autocorrelation of 0.25 with forecasts from the previous period as recommended by Qian et al. (2007a) to simulate stability in forecasts across different time periods. This reflects the intuitive notion that a manager's positive or negative view on a stock will have some consistency over time. Turnover is limited to realistic levels as using a new set of forecasts for each monthly period requires the portfolio to be completely rebalanced, incurring high trading costs.

Costs are factored into the portfolio optimisation algorithm to reflect their impact on portfolio performance.[12] Qian, Hua and Sorensen (2007b) recommend incorporating transaction

[12] The portfolio optimisation algorithm to determine portfolio weights has an objective function that maximises the information ratio after transaction costs and a number of other constraints (e.g., budget, short-selling,

and stock borrowing costs at the portfolio construction stage. The transaction component of the cost function is determined by applying a cost model incorporating commission and spread costs to the change in portfolio weightings.[13] The short position component of the cost function is determined by the proportion of the portfolio short sold, multiplied by the assumed cost of borrowing stock. Including the impact of costs into the portfolio construction model allows the portfolio to be optimised net all costs involved in shorting stocks or portfolio rebalancing. Repeating this process for each generated vector of forecasts is undertaken to provide a set of portfolios for analysis over different assumptions of manager skill, risk tolerance, trading costs and market conditions. The inclusion of a cost model in the portfolio construction is important to provide fair comparison of the performance of active extension funds against long-only portfolios, as they incur a larger implementation cost. The cost function included in the model incorporates transaction costs and costs of borrowing stock. Consistent with Montagu et. al. (2007) and anecdotal evidence from market participants, the base case annual stock borrowing cost is assumed to be 50bps, around 4.2bps on a monthly basis.

This study assumes monthly rebalancing of portfolios, with the transaction cost function applied based on the rebalancing required to meet the new target weights. We begin with an analysis of the performance of active extension portfolios; assuming the base case costs, information coefficient and tracking error target (see Table 1). The assumptions are then varied, with the sensitivity to active extension portfolio performance measured. Sensitivity to variations in skill levels, risk constraints and costs are measured by running a series of optimisations with modifications made to the base-case assumptions. Variation with respect to market conditions, cross-sectional dispersion and volatility are measured by performing a regression analysis on the sensitivity of performance of the active extension portfolios to these factors.

Table 1
A Summary of the Model's Base-case Assumptions

Name	Assumption	Based on
Information coefficient	0.1	Montagu et al. (2007): 0.09 Kroll et al.(2005): 0.05-0.15
Tracking error limit	4%	Montagu et al. (2007): 4% Liodakis (2007): 1-5% Kroll et al. (2005): 4% Martielli (2005): 5%
Commission costs	0.4%	Anecdotal*: 0.4%
Stock borrow costs	0.5%	Montagu et al. (2007): 0.5% White (2007): 0.65% Anecdotal*: 0.5%
Funding spread[11]	0.5%	White (2007): 0.5-0.7%

* Anecdotal evidence was based on discussions with Australian fund managers.

tracking error). The Qian et al. (2007b) algorithm is used, which is based on Kuhn-Tucker conditions for optimisation with inequality constraints.

13 The cost function is provided by Grinold and Kahn (2000) and incorporates both the explicit cost of commissions and market impact costs. It is noted that this cost function is likely to overstate transaction costs. However, considering the aim of this study is to show that active extension portfolios outperform long-only funds; it is preferable to overstate rather than understate transaction costs.

Results

This section summarises the performance of the simulated active extension portfolios relative to long-only portfolios and benchmark returns. Performance statistics are presented as raw returns, excess returns, information ratios and Jensen's alpha, with tests for statistical significance performed on the active performance metrics. The sensitivity of performance to changes in the endogenous and exogenous factors outlined in the hypotheses is measured, including the effect of different skill levels, net execution costs, volatility, cross-sectional dispersion and market conditions.

Performance Overview

Using the base case assumptions 10,000 simulated sets of forecasts were created, from which portfolios were constructed at 11 different levels of short selling for a total of 110,000 portfolios, rebalanced monthly. Table 2 provides an overview of the performance of the simulated active extension strategies. Over the sample period of May 2000 to July 2008, the active extension portfolios outperformed the equivalent long-only and benchmark index returns by a statistically significant margin. The average compound annual growth rate (CAGR) for 130/30 portfolios was 15.2%, compared with 13.3% for long-only funds utilising the same forecasts. The CAGR for the benchmark S&P/ASX 200 Accumulation index by comparison was 10.1%. The performance of active extension portfolios increased with the level of short selling, with 150/50 funds having the highest CAGR of 16.1% compared to the returns for 110/10 of 14.2%. The portfolios with higher levels of short selling had higher information ratios and transfer coefficients, further evidence that relaxing the long-only constraint leads to the construction of more efficient portfolios.

Table 2

The Average Performance of Long-only and Active Extension Funds, Using Base-case Simulation Assumptions

This table presents the mean annualised performance for the simulated portfolios over different levels of short selling. Mean excess return (ER), tracking error (TE) and information ratio (IR) are presented for each set of portfolios. Alpha and beta figures for the median portfolio in terms of performance are also presented. The results are provided before (gross) and after (net) the involved transaction costs and stock borrow costs. Significance tests for information ratios and Jensen's alphas are run under the null hypothesis that risk-adjusted out performance is not greater than zero by a statistically significant level. The significance test for beta identifies whether beta is greater or lower than one by a statistically significant margin. Statistical significance at the 5% and 1% level is represented by * and ** respectively.

	100/0	105/5	110/10	115/15	120/20	125/25	130/30	135/35	140/40	145/45	150/50
Gross ER	3.63%	4.16%	4.52%	4.74%	4.97%	5.32%	5.61%	6.05%	6.29%	6.42%	6.45%
Gross TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
Gross IR	**0.90**	**1.03**	**1.10**	**1.16**	**1.20**	**1.24**	**1.26**	**1.32**	**1.36**	**1.37**	**1.37**
Turnover	39%	42%	44%	45%	46%	49%	50%	52%	55%	56%	58%
Trading costs	0.28%	0.29%	0.31%	0.32%	0.33%	0.34%	0.35%	0.37%	0.38%	0.40%	0.41%
Borrow and funding costs	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%	0.30%	0.35%	0.40%	0.45%	0.50%
Total costs	0.28%	0.34%	0.41%	0.47%	0.53%	0.59%	0.65%	0.72%	0.78%	0.85%	0.91%
Net ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
Net IR	**0.83**	**0.95**	**1.00**	**1.05**	**1.07**	**1.10**	**1.12**	**1.16**	**1.19**	**1.19**	**1.17**
IR t-stat	2.21	2.51*	2.66*	2.77*	2.84*	2.92*	2.96*	3.07*	3.14*	3.14*	3.11*
TC	0.59	0.67	0.71	0.74	0.76	0.78	0.79	0.82	0.84	0.84	0.83
Alpha	**0.0024***	**0.0028****	**0.0077****	**0.0078****	**0.0078****	**0.0082****	**0.0083****	**0.0085****	**0.0088****	**0.0088****	**0.0090****
Beta	1.027	1.014	0.985	0.993	1.023	0.995	1.026	1.032	0.986	1.005	0.967

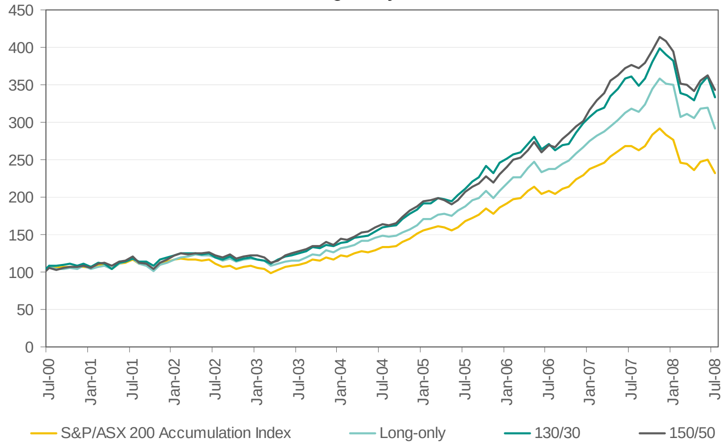
Table 2 shows an increase in the information ratio as the level of short selling is increased, with active extension portfolios utilising higher levels of short selling exhibiting higher risk-adjusted returns. We separately report information ratios net and excluding transaction, borrowing and funding costs. We note that net all costs active extension portfolios continue to outperform equivalent long-only portfolios despite costs reaching as high as an average 0.91% for 150/50 portfolios. Applying a t-test to the realised information ratios shows that the outperformance for the sampled active extension portfolios at 105/5 and above is significant at a 5% level. Using Eq. 2, the transfer coefficients are calculated from the information coefficient, breadth and realised information ratio. The average transfer coefficient for a long-only portfolio is 0.59, implying that 41% of the theoretical unconstrained information ratio is lost to implementation costs and the effects of constraints. Relaxing the long-only constraints leads to an increase in average transfer coefficient, with the 140/40 and 145/45 portfolios returning the highest average transfer coefficients of 0.84.

Although the ex-ante tracking error target was set to 4%, the ex-post tracking error often exceeds this target by an amount that increases at higher levels of short selling. Qian et al. (2007b) identify that a variation in IC over time, representing strategy risk, causes realised tracking error to increase above its target level. Although realised tracking error increases as the level of short selling is increased, on a risk-adjusted basis the information ratio is still higher for larger levels of short positions.

We also compare portfolio performance using Jensen's alpha as a measure of benchmark outperformance after adjusting for systematic risk exposure. The realised alpha and beta for the portfolio with median performance is shown in Table 2. The alphas for all active extension portfolios were greater than zero at a 1% level of significance, while none of the betas were significantly different to one at the 5% level. This indicates that, after adjusting for exposure to systematic risk, the active extension portfolios outperformed the benchmark index, with higher levels of short selling corresponding to higher levels of outperformance. Beta was found to be statistically no different to one, confirming H7 that active extension portfolios have equal performance irrespective of market direction

Figure 1 plots the average performance of the long-only, 130/30 and 150/50 strategies against the benchmark S&P/ASX 200 Accumulation index over the sample period. Each portfolio is rebased to 100 as of the start date. Both long-only and active extension portfolios outperform the benchmark index due to a relatively high assumed information coefficient of 0.1. The active extension portfolios benefit from a relaxation in the long-only constraint and are able to consistently outperform both the long-only portfolios and benchmark index over the sample period.

Figure 1:
Cumulative Performance of Long-only and Active Extension Portfolios



This figure shows that the cumulative performance of active extension portfolios outstrips long-only and benchmark index performance.

Variation in Skill Levels

To model the effect of different skill levels, portfolios are simulated with information coefficients of 0.05, 0.1 and 0.15 to represent managers with low skill, good skill and exceptional levels of skill (as suggested by Grinbold & Kahn 2000).

Table 3
Active Extension Fund Performance Across Different Skill Levels

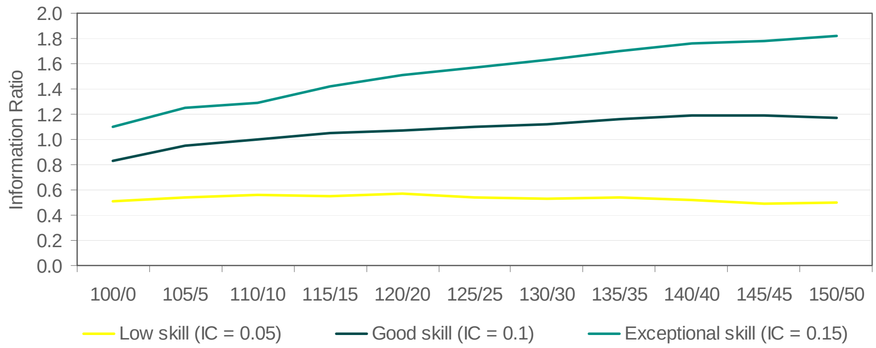
	100/0	105/5	110/10	115/15	120/20	125/25	130/30	135/35	140/40	145/45	150/50
Low skill (IC = 0.05)											
ER	2.03%	2.18%	2.25%	2.23%	2.31%	2.25%	2.24%	2.33%	2.26%	2.17%	2.26%
TE	3.99%	4.01%	4.03%	4.05%	4.09%	4.19%	4.22%	4.28%	4.31%	4.39%	4.51%
IR	**0.51**	**0.54**	**0.56**	**0.55**	**0.57**	**0.54**	**0.53**	**0.54**	**0.52**	**0.49**	**0.50**
TC	0.72	0.77	0.79	0.78	0.80	0.76	0.75	0.77	0.74	0.70	0.71
Alpha	**0.0014**	**0.0018**	**0.0030***	**0.0041****	**0.0050****	**0.0045****	**0.0048****	**0.0050****	**0.0042****	**0.0044****	**0.0047****
Good skill (IC = 0.10)											
ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
IR	**0.83**	**0.95***	**1.00***	**1.05***	**1.07***	**1.10***	**1.12***	**1.16***	**1.19***	**1.19***	**1.17***
TC	0.59	0.67	0.71	0.74	0.76	0.78	0.79	0.82	0.84	0.84	0.83
Alpha	**0.0024***	**0.0028****	**0.0077****	**0.0078****	**0.0078****	**0.0082****	**0.0083****	**0.0085****	**0.0088****	**0.0088****	**0.0090****
Exceptional skill (IC = 0.15)											
ER	4.45%	5.11%	5.32%	5.93%	6.34%	6.77%	7.33%	8.01%	8.61%	8.93%	9.40%
TE	4.03%	4.08%	4.11%	4.17%	4.21%	4.31%	4.49%	4.72%	4.89%	5.01%	5.15%
IR	**1.10***	**1.25***	**1.29***	**1.42****	**1.51****	**1.57****	**1.63****	**1.70****	**1.76****	**1.78****	**1.82****
TC	0.52	0.59	0.61	0.67	0.71	0.74	0.77	0.80	0.83	0.84	0.86
Alpha	**0.0032****	**0.0088****	**0.0089****	**0.0090****	**0.0095****	**0.0103****	**0.0123****	**0.0128****	**0.0137****	**0.0141****	**0.0153****

This table presents the mean annualised performance for the simulated portfolios at different levels of short selling and different skill levels. Mean excess returns (ER), tracking errors (TE), information ratios (IR) and transfer coefficients (TC) are presented for each portfolio, along with computed alphas for the median-performing portfolio. The results are provided on an after costs basis. Significance tests for information ratios and Jensen's alphas are run under the null hypothesis that risk-adjusted out performance is not greater than zero by a statistically significant level. Statistical significance at the 5% and 1% levels are represented by * and ** respectively.

Table 3 summarises the performance of these portfolios segregated by skill level. Across all short selling levels, performance is highest for the portfolio with the largest information coefficient, reflecting superior information content in the generated forecasts.

Relaxing the long-only constraint leads to a greater increase in performance for the 'exceptional skill' portfolio compared to the 'low skill' portfolio. Figure 2 shows this difference graphically. The information coefficient of 'exceptional skill' portfolios increases by 65% moving from a 100/0 to 150/50 makeup, while the information coefficient of the 'low skill' portfolio decreases by 2% for the same shift in short selling. This result confirms H1.

Figure 2
Average Information Ratios Across Skill Levels



This figure shows that managers with exceptional skills exhibit higher average information ratios

Three sets of portfolios over the sample period are constructed to examine how the skew in managerial skill affects the information ratios of active extension strategies. The first portfolio represents managers with equal skill and uses the 10,000 simulated forecasts and associated portfolios that assumed a tracking error of 4% and an information coefficient of 0.1. The second (third) portfolio simulates a manager with a bias in skill towards identifying outperforming (underperforming) stocks for long (short) positions by giving the manager a skill of 0.15 (0.05) in selecting stocks that go on to outperform the index, and a skill of 0.05 (0.15) at selecting underperforming stocks. Table 4 shows the results for all three sets of portfolios. When the long-only constraint was imposed, the portfolio based on long-biased skill outperformed the equal skill and short-biased skill portfolios. However, at 130/30 and above, the equal skill portfolio outperformed the portfolios with bias in skill. The portfolios constructed with long-biased and short-biased skill underperformed the equal skill portfolio at levels of short selling above 130/30. Further, all portfolios with long-biased skill and equal skill are able to outperform the portfolios with short-biased skill at all levels of short selling. These results are not consistent with H2.

Table 4
Performance for Active Extension Funds with Bias in Stock-selection ability

	100/0	105/5	110/10	115/15	120/20	125/25	130/30	135/35	140/40	145/45	150/50
Equal skill											
ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
IR	**0.83**	**0.95***	**1.00***	**1.05***	**1.07***	**1.10***	**1.12***	**1.16***	**1.19***	**1.19***	**1.17***
TC	0.59	0.67	0.71	0.74	0.76	0.78	0.79	0.82	0.84	0.84	0.83
Alpha	**0.0024***	**0.0028****	**0.0077****	**0.0078****	**0.0078****	**0.0082****	**0.0083****	**0.0085****	**0.0088****	**0.0088****	**0.0090****
Long-biased skill											
ER	3.94%	4.26%	4.60%	4.46%	4.39%	4.91%	4.86%	5.31%	5.41%	5.26%	5.42%
TE	4.04%	4.02%	4.12%	4.15%	4.14%	4.51%	4.41%	4.69%	4.72%	4.71%	4.79%
IR	**0.98***	**1.06***	**1.12***	**1.07***	**1.06***	**1.09***	**1.10***	**1.13***	**1.15***	**1.12***	**1.13***
TC	0.69	0.75	0.79	0.76	0.75	0.77	0.78	0.80	0.81	0.79	0.80
Alpha	**0.0035****	**0.0079****	**0.0088****	**0.0086****	**0.0081****	**0.0073****	**0.0075****	**0.0082****	**0.0079****	**0.0095****	**0.0083****
Short-biased skill											
ER	2.17%	2.94%	3.51%	3.95%	4.40%	4.52%	4.63%	5.06%	5.25%	5.04%	5.45%
TE	4.03%	4.08%	4.07%	4.17%	4.38%	4.44%	4.42%	4.65%	4.70%	4.69%	4.76%
IR	**0.54**	**0.72**	**0.86**	**0.95***	**1.00***	**1.02***	**1.05***	**1.09***	**1.12***	**1.07***	**1.15***
TC	0.38	0.51	0.61	0.67	0.71	0.72	0.74	0.77	0.79	0.76	0.81
Alpha	**0.0019***	**0.0021***	**0.003****	**0.0055****	**0.0070****	**0.0069****	**0.0085****	**0.0087****	**0.0089****	**0.009****	**0.0088****

This table presents the mean annualised performance for the simulated portfolios, where stock selection skill is skewed towards picking potential out performers or potential underperformers. Mean excess returns (ER), tracking errors (TE), information ratios (IR) and transfer coefficients (TC) are presented for each portfolio, along with computed alphas for the median-performing portfolio. The results are provided after costs. Significance tests for information ratios and Jensen's alphas are run under the null hypothesis that risk-adjusted out performance is not greater than zero by a statistically significant level. Statistical significance at the 5% and 1% level is represented by * and ** respectively.

Risk Constraints

Five sets of portfolios over the sample period are constructed to examine whether portfolios with higher risk constraints (as measured by tracking error) are likely to benefit more from introducing short selling than portfolios with lower tracking error. 10,000 sets of forecasts were simulated, with long-only portfolios and active extension portfolios constructed over 11 different levels of short selling at 5% intervals with five different levels of tracking error, creating a total sample of 550,00 portfolios that are rebalanced monthly. Table 5 shows the average information ratios and transfer coefficients for the sampled portfolios across different levels of tracking error. The largest excess returns were for the portfolios with higher tracking error and higher levels of short selling, as these portfolios allowed the largest active positions to be taken to reflect the forecast stock returns. The increase in average information ratio from long-only to 150/50 can be seen to be positively related to the level of tracking error in the portfolio. At a 2% level of tracking error, the average information ratio increases from 0.98 for the long-only portfolio to 1.20 for the 150/50 fund. At the 6% level of tracking error, the average information ratio increases from 0.3 to 1.12. This result confirms H3.

Table 5
Average Performance for Long-only and Active Extension funds with Different Tracking Error Targets

	100/0	105/5	110/10	115/15	120/20	125/25	130/30	135/35	140/40	145/45	150/50
2% target tracking error											
ER	1.96%	2.14%	2.24%	2.30%	2.46%	2.51%	2.65%	2.58%	2.65%	2.61%	2.63%
TE	2.01%	2.02%	2.06%	2.06%	2.10%	2.11%	2.13%	2.15%	2.18%	2.20%	2.19%
IR	**0.98****	**1.06****	**1.09****	**1.12****	**1.17****	**1.19****	**1.24****	**1.20****	**1.22****	**1.19****	**1.20****
TC	**0.69**	**0.75**	**0.77**	**0.79**	**0.83**	**0.84**	**0.88**	**0.85**	**0.86**	**0.84**	**0.85**
3% target tracking error											
ER	2.64%	2.83%	3.22%	3.26%	3.35%	3.58%	3.76%	3.91%	3.95%	4.04%	4.20%
TE	3.02%	3.03%	3.08%	3.07%	3.12%	3.20%	3.29%	3.38%	3.41%	3.45%	3.46%
IR	**0.88***	**0.93****	**1.05****	**1.06****	**1.07****	**1.12****	**1.15****	**1.16****	**1.16****	**1.17****	**1.22****
TC	**0.62**	**0.66**	**0.74**	**0.75**	**0.76**	**0.79**	**0.81**	**0.82**	**0.82**	**0.83**	**0.86**
4% target tracking error											
ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
IR	**0.83***	**0.95****	**1.00****	**1.05****	**1.07****	**1.10****	**1.12****	**1.16****	**1.19****	**1.19****	**1.17****
TC	**0.59**	**0.67**	**0.71**	**0.74**	**0.76**	**0.78**	**0.79**	**0.82**	**0.84**	**0.84**	**0.83**
5% target tracking error											
ER	2.41%	3.22%	4.13%	4.39%	4.66%	4.86%	5.21%	5.63%	5.83%	6.06%	6.30%
TE	5.02%	5.06%	5.13%	5.09%	5.15%	5.29%	5.42%	5.60%	5.65%	5.72%	5.71%
IR	**0.48**	**0.64**	**0.81***	**0.86***	**0.91****	**0.92****	**0.96****	**1.00****	**1.03****	**1.06****	**1.10****
TC	**0.34**	**0.45**	**0.57**	**0.61**	**0.64**	**0.65**	**0.68**	**0.71**	**0.73**	**0.75**	**0.78**
6% target tracking error											
ER	1.79%	3.77%	4.45%	4.96%	5.40%	5.74%	6.28%	6.47%	7.03%	7.30%	7.85%
TE	6.03%	6.07%	6.17%	6.15%	6.26%	6.44%	6.63%	6.83%	6.90%	6.98%	7.03%
IR	**0.30**	**0.62**	**0.72***	**0.81***	**0.86***	**0.89***	**0.95****	**0.95****	**1.02****	**1.05****	**1.12****
TC	**0.21**	**0.44**	**0.51**	**0.57**	**0.61**	**0.63**	**0.67**	**0.67**	**0.72**	**0.74**	**0.79**

This table shows the mean excess returns (ER), tracking errors (TE), information ratios (IR) and transfer coefficients (TC) for each level of tracking error for a given level of short selling. Risk-adjusted out performance, as measured by the information ratio, is higher for portfolios with lower levels of tracking error and higher levels of short selling. Significance tests are performed on the information ratios, with * and ** denoting significance levels of 10% and 5% respectively.

The highest information ratios and transfer coefficients were exhibited by portfolios with the lowest tracking error. There was also a comparatively smaller increase in performance by introducing short positions, and a negligible performance benefit in increasing the level of short selling past 30%. As the level of short selling is set as a maximum upper bound, for portfolios with short selling levels above 30%, the portfolio optimiser chose a smaller level of short selling than the maximum, to maximise returns within the relatively low tracking error. For example, there would be little utility in constraining all portfolios to an exact 50% shorting level if the tracking error target was 2%. As a result, there is reduced benefit to increasing short selling in these portfolios past the typical 30% level. Imposing a high level of short selling becomes needlessly restrictive.

Costs

Three sets of portfolios over the sample period are constructed to assess the impact of costs relative to managerial skill on the performance of active extension portfolios. Based on the cost assumptions in Table 6, portfolios are simulated at low, medium and high levels of costs. 10,000 simulated portfolios are created for each cost assumption case at each level of short selling, yielding a total 330,000 sample portfolios that are rebalanced monthly over the sample period. The 'base case' cost assumptions are identical to those used for testing all other hypotheses.

Table 6
Simulation Cost Assumptions

	Low	**Medium (base case)**	**High**
Commission costs	0.20%	0.40%	0.60%
Stock borrow costs	0.25%	0.50%	0.75%
Funding spread	0.25%	0.50%	0.75%

This table presents the mean annualised performance for the simulated portfolios over different levels of short selling. Mean excess return (ER), tracking error (TE) and information ratio (IR) are presented for each set of portfolios. Alpha and beta figures for the median portfolio in terms of performance are also presented. The results are provided before (gross) and after (net) the involved transaction costs and stock borrow costs. Significance tests for information ratios and Jensen's alphas are run under the null hypothesis that risk-adjusted out performance is not greater than zero by a statistically significant level. The significance test for beta identifies whether beta is greater or lower than one by a statistically significant margin. Statistical significance at the 5% and 1% level is represented by * and ** respectively.

Table 7 shows the average realised performance and costs for the sampled portfolios. As the portfolio construction process takes into account the effect of costs during the optimisation process, the portfolios have different weightings and therefore different levels of performance before costs.

Table 7
Sensitivity of Active Extension Performance to Changes in Trading, Borrow and Funding Costs

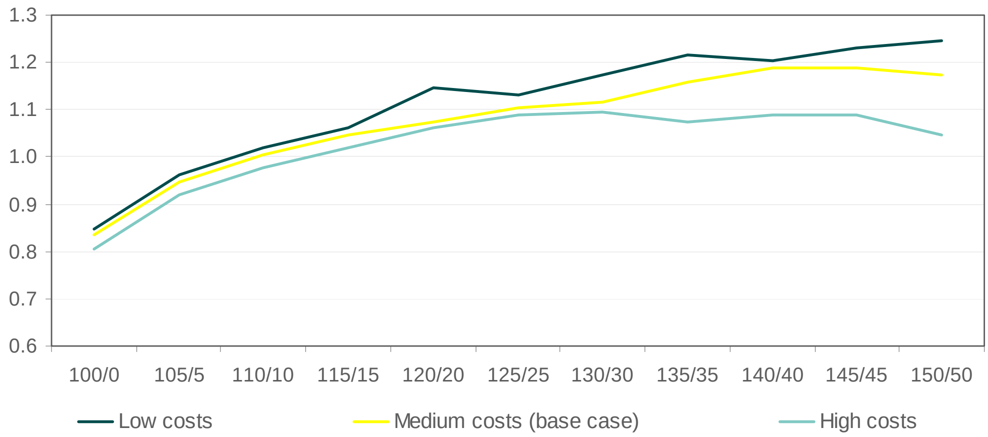
	100/0	**105/5**	**110/10**	**115/15**	**120/20**	**125/25**	**130/30**	**135/35**	**140/40**	**145/45**	**150/50**
Low costs											
Turnover	47%	51%	53%	54%	56%	59%	61%	63%	66%	68%	74%
Trading costs	0.27%	0.28%	0.30%	0.31%	0.32%	0.33%	0.34%	0.36%	0.36%	0.39%	0.42%
Borrow & funding costs	0.00%	0.03%	0.05%	0.08%	0.10%	0.13%	0.15%	0.18%	0.20%	0.23%	0.25%
Total costs	**0.27%**	**0.31%**	**0.35%**	**0.38%**	**0.42%**	**0.45%**	**0.49%**	**0.53%**	**0.56%**	**0.61%**	**0.67%**
ER	3.40%	3.89%	4.16%	4.34%	4.75%	4.84%	5.22%	5.61%	5.54%	5.82%	5.90%
TE	4.01%	4.05%	4.09%	4.09%	4.15%	4.28%	4.45%	4.61%	4.61%	4.73%	4.74%
IR	**0.85***	**0.96****	**1.02****	**1.06****	**1.15****	**1.13****	**1.17****	**1.22****	**1.20****	**1.23****	**1.24****
TC	0.60	0.68	0.72	0.75	0.81	0.8	0.83	0.86	0.85	0.87	0.88
Medium costs (base case)											
Turnover	39%	42%	44%	45%	46%	49%	50%	52%	55%	56%	58%
Trading costs	0.28%	0.29%	0.31%	0.32%	0.33%	0.34%	0.35%	0.37%	0.38%	0.40%	0.41%
Borrow & funding costs	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%	0.30%	0.35%	0.40%	0.45%	0.50%
Total costs	**0.28%**	**0.34%**	**0.41%**	**0.47%**	**0.53%**	**0.59%**	**0.65%**	**0.72%**	**0.78%**	**0.85%**	**0.91%**
ER	3.35%	3.83%	4.11%	4.27%	4.45%	4.73%	4.96%	5.33%	5.51%	5.57%	5.54%
TE	4.02%	4.04%	4.09%	4.08%	4.14%	4.29%	4.44%	4.60%	4.64%	4.69%	4.72%
IR	**0.83***	**0.95****	**1.00****	**1.05****	**1.07****	**1.10****	**1.12****	**1.16****	**1.19****	**1.19****	**1.17****
TC	0.59	0.67	0.71	0.74	0.76	0.78	0.79	0.82	0.84	0.84	0.83
High costs											
Turnover	35%	37%	39%	40%	43%	42%	46%	49%	51%	53%	57%
Trading costs	0.28%	0.29%	0.31%	0.32%	0.33%	0.34%	0.35%	0.37%	0.38%	0.40%	0.41%
Borrow & funding costs	0.00%	0.08%	0.15%	0.23%	0.30%	0.38%	0.45%	0.53%	0.60%	0.68%	0.75%
Total costs	**0.28%**	**0.36%**	**0.46%**	**0.54%**	**0.63%**	**0.72%**	**0.80%**	**0.89%**	**0.98%**	**1.07%**	**1.16%**
ER	3.24%	3.71%	3.99%	4.16%	4.39%	4.66%	4.86%	4.96%	5.05%	5.12%	4.97%
TE	4.02%	4.04%	4.09%	4.09%	4.14%	4.28%	4.44%	4.62%	4.64%	4.70%	4.75%
IR	**0.81***	**0.92***	**0.98****	**1.02****	**1.06****	**1.09****	**1.10****	**1.07****	**1.09****	**1.09****	**1.05****
TC	0.57	0.65	0.69	0.72	0.75	0.77	0.775	0.76	0.77	0.77	0.74

This table presents the mean annualised performance for the simulated portfolios over different levels of short selling over the three cost cases outlined in Table 6. Mean excess returns (ER), tracking errors (TE), information ratios (IR) and transfer coefficients (TC) are presented for each set of portfolios. Performance results are provided after the involved transaction costs and stock borrow costs. Significance tests for information ratios are run under the null hypothesis that risk-adjusted outperformance is not greater than zero by a statistically significant level. Statistical significance at the 10% and 5% level is represented by * and ** respectively.

After including all costs, portfolios with higher costs had lower levels of performance. The portfolios with the highest costs exhibited the largest drop-off in information coefficient as the level of short selling was increased. The highest information coefficient for the 'high costs' portfolios was 130/30, above which the information coefficient dropped due to the higher trading and borrow costs. The 'low costs' portfolio suffers less of a drop-off in performance at higher levels of short selling as the cost drag from increased turnover and borrowing is lower.

Figure 3 shows the information ratios for each set of cost assumptions over different levels of short selling. The implication is that when faced with increased costs, a lower amount of short selling should be used. Additional short positions beyond a certain level will be inefficient due to the higher costs involved. All other factors being equal, higher costs necessitate targeting a lower level of short selling. These results confirm H4.

Figure 3
Average Information Ratios over Different Cost Assumptions



This figure shows that increasing total costs lead to lower average information ratios across a range of active extension portfolios.

Volatility, Cross-sectional Spread and Market Conditions

The effect of exogenous market factors on the performance of active extension portfolios are tested jointly by adding proxies for volatility and cross-sectional spread into a modified CAPM equation given below.

$$R_p - R_f = \alpha + \beta_1(R_m - R_f) + \beta_2\sigma_M + \beta_3\rho_M + \varepsilon \quad (3)$$

where R_p is the portfolio total returns, R_m is the market returns given by the returns on the S&P/ASX 200 Accumulation index, R_f is the risk-free rate given by the 10-year Australian government bond yield, alpha (α) measures the outperformance on a risk-adjusted basis, beta (β) measure the systematic risk. Eq. 3 is an extension of Jensen's (1968) model to measure the effect on performance of active extension portfolios of market-wide volatility (σ_M) and cross-sectional spread (ρ_M), after adjusting for market excess returns (R_m-R_f). The measure of cross-sectional dispersion used is the mean pair-wise correlation of monthly returns. Volatility for the S&P/ASX

200 Accumulation index was measured on a historical 12-month basis. Monthly returns from 10,000 simulated 130/30 portfolios are used, for a total sample size of 990,000 observed monthly returns. Table 8 shows the results of the above regression.

Table 8
Regression Results

Variable	**Coefficients**	**Standard Error**	**T Statistic**	**P-value**
Intercept	0.000	0.000	-1.449	0.147
Market returns	1.015	0.002	432.230	0.000
Market volatility	-0.357	0.198	-1.802	0.071
Pairwise correl.	0.000	0.001	0.005	0.996

Regression Statistics	
R Square	0.950
Adj.R Square	0.950
Standard Error	0.008
F-statistic	62665
Observations	990,000

This table presents the regression results which show the explanatory power of market volatility and cross-sectional dispersion on portfolio performance. Monthly excess returns over the risk-free rate (10-year bond yield) are regressed against market excess returns, market volatility and pair-wise correlations.

The coefficient for market volatility is -0.357, suggesting that monthly outperformance decreases by -0.357% for every 1% increase in 12-month rolling market volatility. This contradicts H5, which put forward that higher market volatility would lead to higher risk-adjusted portfolio performance. The coefficient for pair-wise correlation was close to zero with no statistical significance, implying that pair-wise correlation has no effect on the performance of active extension portfolios. This finding neither confirms nor rejects H6. The observed coefficient for market returns is 1.015, which is statistically significant at the 1% level. This suggests that active extension portfolios outperform the index when index returns are positive and underperform the index when index returns are negative. However, the beta coefficient of 1.015 is only marginally greater than one, implying that the exposure to systematic risk is roughly in line with the benchmark index. This result is also confirmed by the regression results in Table 2, which found that the beta for the active extension portfolios was statistically no different to one.

Conclusions

This study uses simulation analysis to examine the performance of active extension strategies in the Australian equities markets from May 2000 to June 2008. We find that active extension portfolios are capable of outperforming equivalent long-only portfolios and the benchmark S&P/ASX 200 index. Our results build on the previous US based literature of Qian et al. (2007a) and Clarke et al. (2008) by extending the analysis to encompass a different market and examining the effects of additional factors on portfolio performance.

The study finds that the degree to which an active extension portfolio outperforms an equivalent long-only portfolio and the benchmark index is positively related to the level of manager skill and negatively related to the level of costs. Active extension strategies do not generate additional information, but provide managers with the ability to more efficiently use their existing information. Costs have a significant effect on portfolio performance as they tend to increase as the level of short selling in the portfolio is increased. Whether active extension portfolios are able to outperform long-only portfolios depends on whether the forecasting ability of the manager is sufficient to outperform the cost drag. Provided that the manager has reasonable forecasting ability, active extension portfolios outperform equivalent portfolios with the long-only constraint in place. If the manager has little to no skill in stock picking, the net effect of using an active extension strategy will be to decrease performance due to the increased cost drag.

The performance of active extension strategies is also closely related to the targeted level of risk. Funds with lower risk targets benefit little from introducing short-selling, while funds with higher risk targets generally present greater risk/return opportunities than funds concentrated in a small number of long positions. External market conditions such as volatility, pair-wise correlation between individual stocks and market direction are found to have a limited impact on active extension performance.

Overall, the results of this study have a high degree of relevance to institutional fund managers who seek guidance on the appropriate level of short-selling for a fund by quantifying the benefits of introducing short-selling to existing long-only Australian equity portfolios. The results are also highly pertinent to investors seeking to identify whether allocating assets to an active extension fund is appropriate and if so, the characteristics to consider when choosing a fund.

References

Clarke, R, de Silva, H & Thorley, S 2002, 'Portfolio constraints and the fundamental law of active management', *Financial Analysts Journal*, vol. 58, no. 5, pp48-66.

Clarke, R, de Silva, H & Sapra, S 2004, 'Towards more information-efficient portfolios', *Journal of Portfolio Management*, vol. 31, no. 1, pp54-63.

Clarke, R, de Silva, H, Sapra, S & Thorley, S 2008, 'Long-short extensions: How much is enough?', *Financial Analysts Journal*, vol. 64, no. 1, pp16-30.

Foley, T 2006, 'Relaxing the Long-only constraint in U.S. equity strategies', *Journal of Investing*, vol. 15, no. 3, pp79-89.

Gastineau, G 2008, 'The short side of 130/30 investing for the conservative portfolio manager', *Journal of Portfolio Management*, vol. 34, no. 2, pp39-52.

Grinold, R 1989, 'The fundamental law of active management', *Journal of Portfolio Management*, vol. 15, no. 3, pp30-37.

Grinold, R & Kahn, R 2000, *Active Portfolio Management - A Quantitative Approach for Producing Superior Returns and Controlling Risk:* 2nd edn, McGraw-Hill.

Jacobs, B & Levy, K 2006, 'Enhanced active equity strategies: relaxing the long-only constraint in the pursuit of active return', *Journal of Portfolio Management*, vol. 32, no. 3, pp45-55.

Jensen, M 1968, 'The performance of mutual funds in the period 1945-1964', *Journal of Finance*, vol. 23, pp389-416.

Kroll, B, Trichilo, D & Braun, J 2005, 'Extending the fundamental law of investment management', JP Morgan Asset Management – Equity Insights

Liodakis, M 2007, 'Searching for alpha: Is 130/30 optimal?', Citigroup Investment Research

Martelli, J 2005, 'Quantifying the benefits of relaxing the long-only constraints', *SEI Investments*, accessed 15/7/2008, http://www.seic.com/institutions/General_Investment_Research.asp

Montagu, C, Cahan, R & Morton, N 2007, 'Relaxing the long-only constraint: gearing up your alpha for the same beta', Citigroup Investment Research

Patterson, S 2006, 'A strategy aiming to pump returns gains clout but may be "no free lunch"', *Wall Street Journal*, 13October, C1.

Qian, E, Hua, R & Sorensen, E 2007a 'Information horizon, portfolio turnover, and optimal alpha models', *Journal of Portfolio Management*, vol. 34, no. 1, pp12-22.

Qian, E, Hua, R & Sorensen, E 2007b, *Quantitative Equity Portfolio Management: Modern Techniques and Applications*, Chapman & Hall.

Sorensen, E, Hua, R & Qian, E 2007, 'Aspects of constrained long-short equity portfolios', *Journal of Portfolio Management*, vol. 33, no. 2, pp12-22.

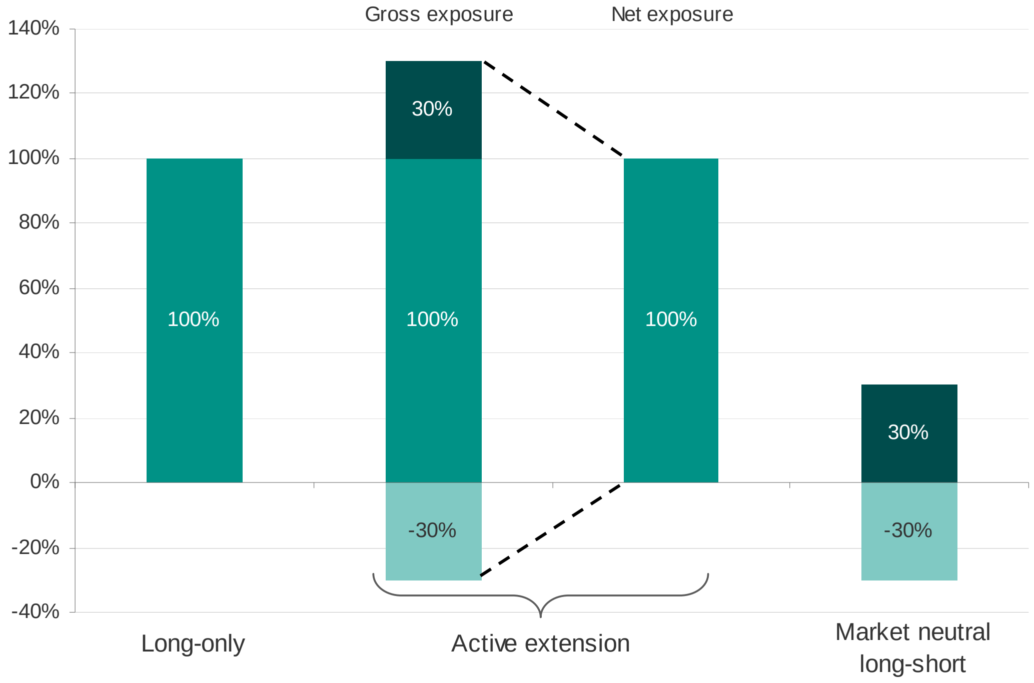
White, A 2007, 'The new 130/30: An alternate approach to implementing enhanced long strategies', Index Research Group

Appendix 1

A Comparison of Active Extension Strategies to Similar Equity Portfolios

The structure of an active extension portfolio relative to similar equity portfolios (i.e., long-only and market neutral long-short portfolios) is shown in Figure A.1. Unlike a long-short portfolio style traditionally adopted by hedge funds, the active extension portfolios are fully invested in the market at all times and do not seek to generate excess returns by market timing. Instead, the benefit of the strategy comes from removing the long-only constraint and introducing the ability to short-sell stocks.

Figure A.1: Comparison of active strategies



This figure compares the structures of long only, 130/30 active extension and market neutral long-short strategies.

Active extension strategies are typically benchmarked to an equity index to reflect their full exposure to the market, unlike traditional market neutral long-short strategies, which are often measured against a total return benchmark such as the cash rate. By relaxing the long-only constraint managers are able to fully utilise their views on stocks they expect to underperform as well as taking additional positions in stocks they expect to outperform.

Although active extension funds are sometimes viewed as a type of hedge fund strategy due to the short-selling employed, in practice they have greater similarities to traditional long-only equity portfolios with the addition of greater flexibility and efficiency. Most active extension funds have mandates to take positions in equities only and do not invest in the wide range of assets in which some hedge funds invest. Active extension strategies have return characteristics that are closer to long-only funds than market-neutral funds, as they have 100% net exposure to equities at all times and are typically benchmarked to a market index. However, similarities exist between the fee structures seen in active extension funds and hedge funds. Active extension funds, like hedge funds, often charge a performance fee in addition to a base fee that is typically higher than that charged by long-only funds. Table A.1 highlights the key differences between active extension strategies and other similar equity portfolios.

Table A.1
Overview of Similar Equity Active Management Strategies

	Long-only	**Active extension**	**Market Neutral Long-Short**
Investment style	Relative return	Relative return	Absolute return
Benchmark	Market index	Market index	Cash rate/hurdle rate
Net exposure	100%	100%	0%
Gross exposure	100%	160%[a]	Variable
Target beta	1	1	0
Short selling	None	30%[a]	Variable
FUM[b]	US$63.7t	US$53.3b	US$2.48t
Typical management fee[b]	30-80bp	60-150bp	>150bp
Performance fee	Usually 0%	0-20%	Typically 20%
Introduced in:	Mid-1800s	Late 1990s	1949

[a] The percentage given assumes a typical 130/30 structure
[b] The Funds Under Management (FUM) and typical management fees are approximate estimates based on industry reports in late 2008.